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ABSTRACT

An important but too infrequently considered methodology that can be used in research, especially research focusing on Pearson's "r" (B. Walsh, 1996) or the multiple "R" (see B. Thompson, 1992) involves testing for moderator or mediator variable effects. As explained by M. Gall, W. Borg, and J. Gall (1996), moderator analysis "involves identifying a subgroup for whom the correlation between a criterion and a predictor variable is significantly greater than the correlation for the total sample from which the group was formed" (p. 425). A study by M. Zeidner (1987) provides a concrete example of this methodology. Zeidner studied the relationship between aptitude test performance and grade point average. However, he believed that this relationship would be moderated by age (be different across age groups). Therefore, he computed "r" across four different age groups, and found that values differed considerably across age, as expected. Techniques for evaluating these effects are explained and illustrated. In a sense, these dynamics can be related to the "restriction of range" effect (an influence on "r" caused by the variance in the sample; correlation will increase or decrease depending on the range of subjects studied) so widely misunderstood within the social sciences. (Contains 2 figures and 17 references.) (Author/SLD)

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Illustrations of the Basic Concepts Involved in Testing for Moderator/Mediator Variable Effects

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Abstract

An important but too infrequently considered methodology that can be employed in research, especially research focusing on Pearson r (Walsh, 1996) or the multiple R (cf. Thompson, 1992), involves testing for moderator or mediator variable effects. As explained by Gall, Borg and Gall (1996), moderator analysis

> involves identifying a subgroup for whom the correlation between a criterion and a predictor variable is significantly greater than the correlation for the total sample from which the group was formed. (p. 425)

A study by Zeidner (1987) provides a concrete example of this methodology. Zeidner studied the relationship between aptitude test performance and GPA. However, he believed that this relationship would be moderated by age (i.e., be different across age groups). Therefore, he computed r across 4 different age groups, and found that, indeed, values differed considerably across age, as expected. Techniques for evaluating these effects will be explained and illustrated in the paper. In a sense, these dynamics can be related to the "restriction of range" (an influence on r caused by the variance in the sample; correlation will increase or decrease depending on the range of subjects studied.) effect so widely misunderstood within the social sciences (Walsh, 1996).

Illustrations of the Basic Concepts Involved in Testing for Moderator/Mediator Variable Effects

In the social sciences, testing a hypothesis of the simplest form considering only one independent variable and one dependent variable is not usually reasonable, because typically more complex relationships exist. Therefore, hypotheses should typically test additional variables and more complex relationships in order to provide a more accurate description of the nature of reality.

As a point-in-fact, one of the key issues facing psychotherapy research is that practicing clinicians have maintained that treatments identified by such research are of little value in the real world (Weisz, Donenberg, Han, & Weiss, 1995). Some of the noteworthy issues identified by Weisz et al. include: (a) homogeneity of subjects, (b) narrow problem focus (i.e., no co-morbidity), (c) single, focused treatment method, and (d) structured (guided by manuals and monitored for) adherence to the treatment plan. In other words, variables which might have a noteworthy effect on treatment outcome in the real world, may not have been a noteworthy factor on the outcome of the same treatment when assessed in a research environment.

Friedman (1997) noted that a primary focus of research is the internal and external validity of any outcome. Internal validity has to do with the extent to which the research or evaluation designs make it possible for a clear relationship to be drawn between the independent variable (intervention), and the dependent variable(s) (outcome(s)). The stronger the relationship between the treatment (independent variable) and outcome (dependent variable), the more confidence one can vest in the efficacy and effectiveness of the intervention. External validity focuses on the generalizability of the findings

beyond the conditions of the study. Because relationships between independent and dependent variables are inherently more complex than a single independent variable and its relationship to a single dependent variable, it follows then that, in order to better clarify that relationship (internal validity), the identification of additional variables affecting that relationship must also be considered. Likewise, it also follows that if conclusions are to be drawn concerning the generalizability of treatments in the real world, research designs (in particular those dealing with the social sciences) must also address the multidimensional nature of the relationships between independent and dependent variables. Several authors (Guetzkow & Forehand, 1961; Saunders, 1954; Zedeck, 1971) have noted that the classic validation model, which provides a simple index of the relationship between predictor and criterion, ignores noteworthy factors intervening between behaviors on the two variables.

"Mediator" and "moderator" variables have long been studied for their influence on the predictive validity of interventions in the social sciences; however, researchers continue to display non-uniformity in their application (Baron & Kenny, 1986; James & Brett, 1984). The purpose of the present paper is to clarify for the neophyte researcher the roles of these "third variables" in terms of (a) their relationships with the independent and dependent variables, (b) to identify distinctions between the two, (c) to present methods for determining their presence, and (d) to identify issues associated with their determination.

Definitions

Zedeck (1971) identified a new validation model (moderator model) which allows for (a) predictors to be differentially valid for different groups of individuals, (b) similar job

behaviors to be predictable by different patterns of interactions between predictors and individuals, and (c) similar job behaviors to have differential organizational consequences depending on the situation. For example, Zeidner (1987) investigated the effectiveness of scholastic aptitude tests in predicting collegiate success in older students. First, participants were classified into five subgroups based on age and product moment correlation coefficients (Pearson r) for aptitude test scores were computed by age; then data across age groups were pooled to allow for consideration of a single regression model in predicting GPA. In this manner Zeidner demonstrated that age interacts with aptitude test scores in predicting GPA. In essence, the ability of the scholastic aptitude test to predict collegiate success is moderated by age. In more general terms, Baron and Kenny (1984) define a moderator as

> a qualitative (e.g. race, sex, class) or quantitative (e.g. level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable. (p. 1174)

As represented in Figure 1, the moderator model has three causal paths: the impact of the predictor (Path a), the impact of the moderator (Path b), and the interaction of the product of the two (Path c). The moderator exists if the interaction (Path c) is significant.

Foschi (1997) identified basically three ways of making a hypothesis more complex in the number of variables it includes, two of which are: (a) add either more independent variables or more dependent variables, or both; and (b) incorporate intervening (or mediator) variables, a technique that consists of creating a chain of relationships, with the independent variable at one end of the chain and the dependent variable at the other. For example, one could propose that upon reaching adolescence, youth are predisposed to

risk-taking, and the outcome of those risk-taking behaviors is teen pregnancy. In this case the degree of risk-taking is the intervening mediator variable. More intervening variables, such as substance abuse, can be added to the chain, resulting in a longer chain. From an industrial and organizational perspective, James and Brett (1984) describe a mediation model as the influence of an antecedent transmitted to a consequence through an intervening mediator.

How to Detect a Moderator

According to Saunders (1954), moderator variables have been studied for many years in economics and agriculture and were first used in psychology by Gaylord and Carroll (1948). They called a moderator a "population control variable." Zedeck (1971) noted that other names the moderator variable has been called include "subgrouping variable," "referrent variable," "predictability variable," "modifier variable," and "homolizer variable." Moderator variables are typically introduced when there is an unexpectedly weak or inconsistent relation between a predictor and a criterion variable (e.g., a relation holds in one setting but not in another, or for one subpopulation but not for another).

To determine moderator effects, Baron and Kenny (1986) indicated that the technique for measurement depends on the level of measure of the independent variable and the moderator variable. The four possible scenarios and their suggested technique for identifying moderator effects are:

Case 1: Both moderator and independent variables are dichotomous categorical variables.

Case 1 is the simplest and Baron and Kenny suggest a 2 x 2 ANOVA, with moderation indicated by an interaction effect.

Case 2: The moderator is a dichotomous categorical variable and the independent variable a continuous variable (e.g., gender might moderate the effect of intentions on behavior). In Case 2, moderation may be indicated by correlating the independent variable (intentions) with behavior separately for each gender, and then test the difference.

Case 3: The moderator is a continuous variable and the independent variable is a dichotomous categorical variable. In Case 3, the researcher must know a priori how the effect of the independent variable varies as a function of the moderator. Assuming a linear effect (may also be quadratic or a step function), the linear hypothesis is tested by adding the product of the moderator and the dichotomous independent variable to the equation. Moderator effects are indicated by the statistically significant effect of XZ while X and Z are controlled.

Case 4: Both variables are continuous variables. Assuming the effect of the independent variable (X) and the dependent variable (Y) varies linearly with respect to the moderator (Z), the product variable approach described in Case 3 can be used.

A variable Z is a moderator if the relationship between two (or more) variables, say X and Y, is a function of the level of Z. This definition indicates an X by Z interaction, or a nonadditive relation, where Y is regarded as a probabilistic function of X and Z (James & Brett, 1984). Darrow and Kahl (1982) note that using the technique of Peters and Champoux (1979), a moderator effect will manifest itself as a relationship between the dependent variable and the cross product of the independent and moderator variables, allowing the postulation of relationships between variables. Using Zedeck's (1971) steps

for determining a moderator as "the correlations, slopes, and standard errors of estimate should be examined for the following three regression equations:

(1) $Y = B_0 + B_{1X} + \text{error}$

(2) $Y = B_0 + B_{1X} + B_{2Z} + \text{error}$

where Z is the potential moderator but is treated as an independent predictor, and

(3) $Y = B_0 + B_{1X} + B_{2Z} + B_{3XZ} + \text{error}$

If equations 2 and 3 are significantly different from equation 1, but not from each other, then the variable is an independent predictor and not a moderator variable" (p. 306). (Darrow & Kahl, 1982). They also identify the need to distinguish between mixed and pure moderators. The "pure" moderator is identified by the following regression equation,

$$Y = B_0 + B_1X + B_2X + \text{error}$$

where the moderator variable, Z, occurs only in the interaction term with the independent variable, X. The mixed moderator is identified by the following regression equation,

$$Y = B_0 + B_1X + B_2ZX + B_3Z$$

where the moderator variable appears both in the interaction term and as an independent predictor.

Whether a clear distinction between a "pure" and "mixed" moderator variable can be made depends on the measurement scale of the independent variable, (i.e., feet or meters). For a clear and useful distinction to be made, the independent variable must have a natural zero independent of the measurement scale. Darrow and Kahl (1982) also noted that, in the case of a weak interaction effect, detection of moderators will be less ambiguous when the moderator is pure Vs mixed (i.e., is the variable not a moderator or

is it a mixed moderator). Therefore, this article will limit itself to only addressing the pure form of moderator.

In arguing that to best detect the presence of a moderator variable, the strength of the moderator relationship and the distribution of the moderator variable were both required. Darrow and Kahl compared two techniques for the detection of moderators: Saunders (1956) sub-group analysis technique giving preferential claim to the main effect and a modified regression technique developed by Blood and Mullet (1977) which gives preferential claim on any covariance with the dependent variable that is shared by the main effect (Z) and the moderator effect (XZ) to the moderator effect. The Saunders technique is based on equations 1, 2, and 3, with a moderator effect indicated by a statistically significant difference between regression equations 2 and 3 and no statistically significant difference between regression equations 1 and 2. The Blood and Mullet technique is based on the following three regression equations:

(4) $$Y = B_0 + B_{1X} + \text{error}$$

(5) $$Y = B_0 + B_{1X} + B_{2XZ} + \text{error}$$

(6) $$Y = B_0 + B_{1X} + B_{2XZ} + B_{3Z} + \text{error}$$

with a moderator effect indicated by a statistically significant difference between the equations 4 and 5 but not between 5 and 6.

Results of the Darrow and Kahl study indicate that (a) ability to detect moderators increases as the strength of the effect increases; (b) ability to detect moderators decreases as the error variance increases; and (c) ability to detect moderator decreases as the distribution of the moderator becomes more peaked or centered. In terms of the comparison of Saunders Vs Blood and Mullet:

- For the pure moderator case: (1) neither of the methods gives a high likelihood of detecting a moderator except when the error variance is small relative to the strength of the effect; (2) there is little difference between the two methods in those cases where a reasonable probability of detecting a moderator effect exists.
- It is also important to note that the findings suggest that the strength of the effect of moderators may be most important in detecting their presence. To overcome this problem the Blood and Mullet technique introduces the interaction term into the equation before the main effect of the independent variable.
- As a note of caution, because the Saunders technique requires splitting the sample into sub-groups, in the case where the moderator is naturally continuous, the sub-grouping may result in loss of information.

For straightforward presentation, ease of interpretation, and recommended technique based on a comparison study results, the Blood and Mullet (1977) approach is perhaps a good technique for the beginner "moderator detective".

Is the moderator the same as a suppressor variable? Adding a third variable to the battery of predictors can cause a statistically significant increase in Multiple R. However, Saunders (1954) points out that a moderator variable may be different from a suppressor variable, though they both have zero zero-order relation to the criterion.

How to Determine Mediator Effects

In general, a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion ($x \rightarrow m \rightarrow y$, where x is the predictor (independent variable), m is the mediator, and y is the criterion (dependent variable)). Mediation is best done in the case of a strong relation between the predictor

and the criterion variable. To clarify the meaning of mediation a path diagram depicting a causal chain is shown in Figure 2.

A variable functions as a mediator when it meets the following conditions: (a) variations in levels of the independent variable account for variations in the presumed mediator (Path a); (b) variations in the mediator account for variations in the dependent variable (Path b), and (c) when Paths a and b are controlled, previously statistically significant relationships between the independent and dependent variables are no longer statistically significant, with the strongest demonstration of mediation occurring when Path c is zero. A single, strong mediator is indicated when Path c is reduced to zero. If Path c is not zero, there is indication of multiple possible mediating factors. Because in the "real world" social phenomena have multiple causes, a more realistic goal may be to seek mediators that significantly reduce the direct relation between independent and dependent variable (Path c), rather than to eliminate the relationship altogether (Baron & Kenny, 1986)

To test for mediation, Baron and Kenny suggested estimating a series of regression models as follows: first, regressing the mediator on the independent variable; second, regressing the dependent variable on the independent variable; and third, regressing the dependent variable on both the independent variable and on the mediator. Steps to determining mediator effects might include:

1. Develop a hypothesis, identifying an antecedent and a consequence. Define a priori predictions (James & Brett, 1984).

2. Determine whether analytic procedures associated with exploratory (i.e. correlational) analysis, such as hierarchical regression and/or partial correlation or confirmatory analysis (e.g. path analysis) should be employed (James & Brett, 1984).
3. Perform regression analyses. (In using multiple regression to estimate a mediational model requires assumptions that there is no measurement error in the mediator and that the dependent variable not cause the mediator (Baron & Kenny, 1986), (i.e., $r_{xm} = 0$).
4. Observe regression line slopes.
5. To establish mediation, the following conditions must hold: first, the independent variable must affect the mediator in the first equation; second, the independent variable must affect the dependent variable in the second equation; and third, the mediator must affect the dependent variable in the third equation. If these conditions all hold in the predicted direction, then (for mediation to be occurring), the effect of the independent variable on the dependent variable must be less in the third equation than in the second. Perfect mediation exists if the independent variable has no effect on the dependent variable when the mediator is controlled (Baron & Kenny, 1986).

For a more detailed explanation of mediator effects, the reader is referred to the Baron and Kenny (1986) and James and Brett (1984) articles.

Differences Between Mediator and Moderator

Several distinctions between mediator and moderator variables include:

1. Unlike the mediator-predictor relation (where the predictor is causally antecedent to the mediator), moderators and predictors are at the same level in regard to their role as causal variables antecedent to certain criterion effects. That is, moderator variables

always function as independent variables, whereas mediating events shift roles from effects to causes depending on the focus of the analysis (Baron & Kenny, 1986).

2. A moderator is represented by a single, nonadditive, linear function in which it is desirable to have minimal covariation between the moderator and both the independent and dependent variables. On the other hand, mediation models must be represented by at least two additive, linear functions in which it is desirable to have high degrees of covariation between the mediator and both the antecedent(s) and consequence(s) (James & Brett, 1984).
3. Moderation carries no connotation of causality, whereas mediation implies at the minimum a causal order, and often additional causal implications are required to explain how mediation occurred (James & Brett, 1984). Mediators explain how and why external physical events take on internal psychological noteworthiness; whereas, moderator variables specify when certain effects will hold (Baron & Kenny, 1986).
4. Typically, the moderator model uses the terms independent and dependent variables; the mediator model uses the terms antecedent and consequence (James & Brett, 1984).

Let us look at an example which includes mediating and moderating variables. March and Curry (1998) offered a hypothetical model for predicting treatment outcome using the General Linear Model (GLM) rubric. The full model was framed as:

Hf: *Treatment outcome = Constant + Treatment + Moderator + mediator +*

(Treatment x Moderator +Treatment x Mediator) +

(Treatment x Moderator x Mediator) + Error

The alternative or restricted model, which includes only the constant and the error term, states that "no identified predictor variable, including the specified treatment, has any effect on the dependent variable:

Hr: *Treatment outcome = Constant + Error*

On the left-side of the equations, the outcome of treatment is the primary criterion or dependent variable (DV). On the right-hand side of the equations are various predictors of independent variables that are used to predict treatment outcome. The constant consists of whatever given value would predict the dependent variable (outcome) in the absence of any substantive predictors; or the constant may also include fixed factors that do not vary or that vary consistently across all subjects. What is of interest in analysis is variance. Unplanned, random events which may occur to affect the data (unexplained variance) are attributed to the error component. The remaining variance lies with measured predictors and their interactions.

In the March and Curry (1998) article, treatment was the independent variable or predictor and, as such, was designed to affect the outcome of the dependent variable. The larger the effect of treatment on outcome, the greater the statistical power in the study, (i.e., greater likelihood of finding a difference in outcome between groups differing in levels or types of treatment). However, other variables, because of their relationships with the independent and dependent variables, may affect the treatment outcome. These variables, when considered a priori and controlled and measured as part of the study, are the moderator and mediator variables.

Recalling that a moderator variable is one which affects the direction and strength of the relationship between the independent variable and dependent variable and a mediator

variable explains the relationship between an independent and dependent variable, March and Curry (1998) presented the scenario of a hypothetical psychosocial treatment for panic disorder in which the treatment is much more effective for girls than for boys. In this case, gender is the moderator variable in the prediction model. Following this same scenario (recalling that a mediator explains the relation between the independent and dependent variable), if the gender difference in treatment effectivess is attributable to gender differences in reactance, then reactance is a mediator. The moderator effect of gender is explained by a mediator effect.

Can Moderators be Mediators?

James and Brett (1984) noted that mediation relations may involve a moderator, in which case the mediation relations cannot be additive. However, while making this declaration James and Brett also pointed out that moderators and mediators have different roles, even though they may occur jointly in the same model. They term such models as *moderated mediation* to denote that mediation relations are contingent on the level of a moderator. To further muddy the water, after providing formulas, definitions, and subsequent comparisons to facilitate distinguishing moderators and mediators, James and Brett later provided scenarios to demonstrate how the same mediator variable may, in turn be a moderator variable. To make some sense of the whole exercise, they then summarized that, to avoid confusion, one must remember that it is the role or roles that a variable plays that determine whether the variable is a moderator, a mediator, or both. They noted that, "Thus, applying the definitions for mediation, moderation, and moderated mediation to the operational role(s) played by a variable in each functional relation and equation over the set of relations and equations in a causal system furnishes

the basis for ascertaining whether the variable is a mediator, moderator, or both a mediator and a moderator" (p. 316).

Issues with Employing Mediator and Moderator Models

Several key issues in detecting these effects can be noted. First, the inclusion of moderator and mediator variables in the equation quickly multiplies the number of potential predictors. Following the rule of thumb that multivariate statistics require at least 10 subjects per predictor (Cohen, 1977; Maxwell & Delaney, 1990), the number of participants required to conduct a simple study becomes very large. One treatment with one mediator and one moderator would require at least 30 participants, and if interactions are considered as predictors, the number would increase to at least 60 (March & Curry, 1998).

Second, additional components of outcome add to the complexity of the treatment design when attempting to identify mediator and moderator effects. If the General Linear Model is utilized, several linear models may be required to clarify the picture, since moderators and mediators may interact differently in each model to affect the relationship between independent and dependent variables. Therefore, more complex statistical analysis procedures beyond the regression model may be required (e.g., a canonical model with multiple dependent variables on the left side of the equation and multiple independent variables on the right (March & Curry, 1998).

Zedeck (1971) identified four problems with moderator techniques:

- Cross-validation. Cross-validation is necessary in moderator research but is frequently not done.

- Differential validity among predictability subgroups. Investigators have used three methods for demonstrating differential validities: (a) significantly different coefficients between subgroups (i.e., r_{x1y} is significantly different from r_{x2y}); (b) patterns of validity coefficients reveal some coefficients to be significantly different from zero (i.e., $r_{y \cdot x1x2}$ is significantly different from zero, but r_{x3y} is not); and (c) the validity coefficient of a subgroup is different from the validity coefficient of the total group. Different methods yield differing results.
- Number of subgroups formed. Infinite subgrouping is related to the problems of sample size (i.e., subgroup sample sizes become too small to perform statistical significance testing).
- Validity coefficient of the original total sample. While the basic purpose of any moderator variable approach is to improve validity in situations in which predictors are poor, whether a gain is worth the effort involved in applying a technique is a decision that must be made by the researcher.

SUMMARY

The presentation of the effects of mediator and moderator variables on the relationship between the independent and dependent variables is a necessary but difficult task. The technique suggested here is the moderated regression technique of Blood and Mullet (1971). However, the sub-group analysis may be just as effective when dealing with naturally occurring dichotomous subgrouping.

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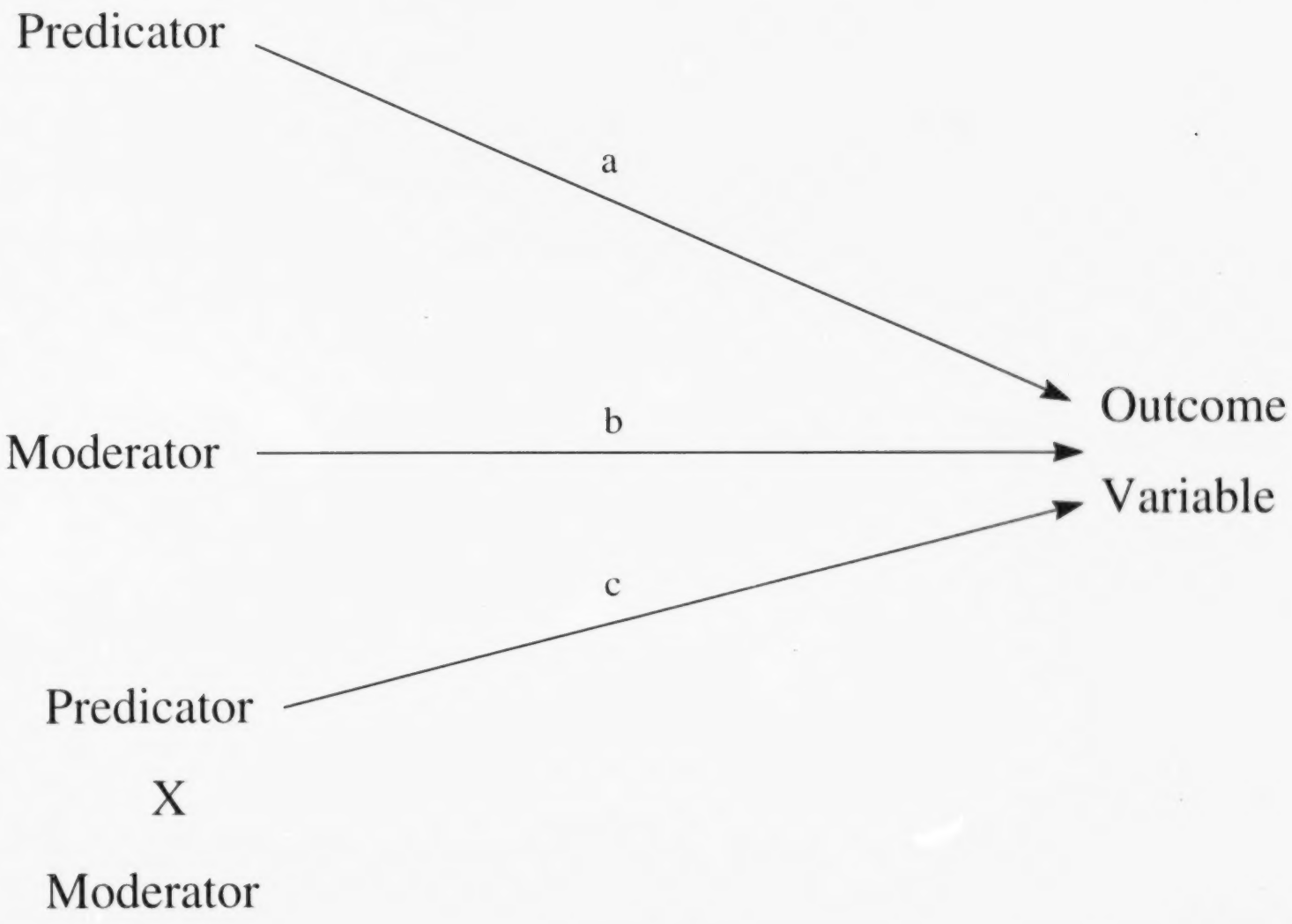

Figure 1. Moderator model

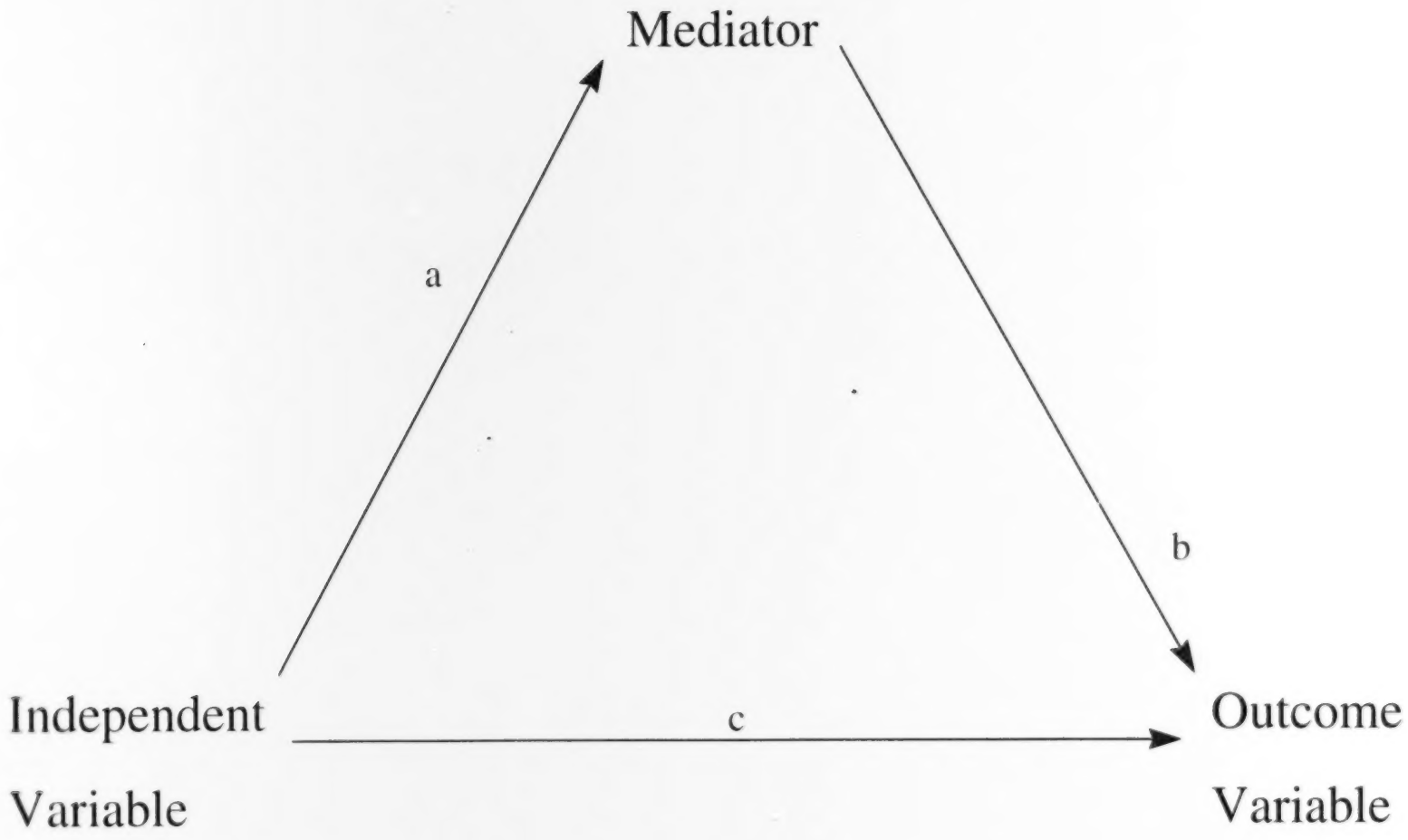

Figure 2. Mediational model